Sugar-Sweetened Beverages and Their Role in Obesity Prevention Programs and Policies

SUGAR-SWEETENED BEVERAGES AND THEIR ROLE IN OBESITY PREVENTION PROGRAMS AND POLICIES

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Abstract

It is well established that sugar-sweetened beverages (SSBs) are associated with obesity and chronic diseases. Although there is some emerging evidence that consumption of added sugars is declining in the United States, on average Americans' consumption still exceeds recommended levels. Consequently, it is imperative that researchers continue to delve further into the question of exactly how SSBs influence obesity and associated chronic diseases, as well as consider creative and novel strategies for reducing their impact on consumers' health.

Several important gaps in the research are addressed by this dissertation. Chapter one considers the role of SSBs and overall diet quality with respect to the growing body of evidence that demonstrates an association between sleep duration and obesity. We used linear regression to examine the associations of sleep duration with dietary indicators in elementary school students taking part in a multi-sector, community-based obesity prevention intervention (the Massachusetts Childhood Obesity Research Demonstration Project). We found that students who reported sleeping <10 hours/day consumed soda more frequently and vegetables less frequently compared with students who reported optimal sleep.

Chapter two assesses whether fast food customers are worse at estimating the caloric content of their meal when their purchase includes a high-calorie beverage (HCB). We used linear regression to examine the association between purchasing HCB and calorie estimation among adult and adolescent fast food customers, and found that among adults, drinking HCB contributes to underestimating calories. HCB may be influencing calorie estimation in a unique way compared to high-calorie food items.

Chapter three considers the relevance of SSBs with respect to proposed changes to the Supplemental Nutrition Assistance Program (SNAP). Using sales data from a large supermarket chain in the Northeast, we used multivariate analysis of variance to determine whether there is an association between SNAP receipt and shopping patterns. We found that SNAP shoppers spent more than non-SNAP shoppers on sugar-sweetened beverages, red meat, and cold convenience foods, and spent less on fruits, vegetables and poultry.

Each chapter lends additional support for a focus on SSB consumption in obesity prevention efforts and will inform the development of prevention strategies in the future.

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Chapter 1:

Insufficient sleep among elementary and middle school students is linked with elevated soda consumption and other unhealthy dietary behaviors

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Abstract

Objective: This study examines the extent to which insufficient sleep is associated with diet quality in students taking part in the Massachusetts Childhood Obesity Research Demonstration Project.

Methods: Data were collected in Fall 2012 for all 4th and 7th grade children enrolled in public schools in two Massachusetts communities. During annual BMI screening, students completed a survey that assessed diet, physical activity, screen time, and sleep. Of the 2456 enrolled students, 1870 (76%) had complete survey data. Generalized estimating equations were used to examine associations between sleep duration and dietary outcomes (vegetables, fruit, 100% juice, juice drinks, soda, sugar-sweetened beverages and water), accounting for clustering by school. Models were adjusted for community, grade, race/ethnicity, gender, television in the bedroom, screen time, and physical activity.

Results: In adjusted models, students who reported sleeping <10 hours/day consumed soda more frequently (β=0.11, 95% CI:0.03, 0.20) and vegetables less frequently (β=-0.09, 95% CI:-0.18, -0.01) compared with students who reported $\geq$10 hours/day. No significant associations were observed between sleep duration and fruit, 100% juice, juice drinks or water.

Conclusions: In this population, insufficient sleep duration was associated with more frequent soda and less frequent vegetable consumption. Longitudinal research is needed to further examine these relationships.

Introduction

The prevalence of childhood obesity remains high in the United States, with approximately one in five children classified as obese and one in three classified as overweight or obese (Ogden et al. 2014). In considering reasons for this high prevalence, there is accumulating evidence that insufficient sleep is a risk factor for obesity (Hu 2008; Taveras, Gillman, et al. 2014b; Hart et al. 2011; Patel & Hu 2008). The National Sleep Foundation recommends 10 to 11 hours of sleep for children ages 5 to 12 (National Sleep Foundation n.d.). However, according to the 2014 Sleep in America poll, 31% of children aged 6-11 years sleep less than 9 hours per night (National Sleep Foundation n.d.). There are a variety of potential mechanisms whereby insufficient sleep may increase risk of obesity, including increased hunger, opportunity to eat, altered thermoregulation, and fatigue (Hu 2008), as well as reduced executive function and inhibition (Burt et al. 2014; Sadeh et al. 2002). More specifically, metabolic effects of sleep deprivation include abnormalities in appetite regulatory hormones that may lead to increased appetite, including lower leptin (an appetite suppressant) and higher ghrelin (an appetite stimulant) (Hu 2008). Given the apparent relationship between sleep deprivation and obesity, there is a growing interest in targeting sleep as a component of obesity interventions (Taveras et al. 2012).

In addition, there is a substantial body of evidence that demonstrates the association between diet quality and obesity (Hu 2008). For example, it has been well established that sugar-sweetened beverages (SSBs) are associated with weight gain (Malik et al. 2013; de Ruyter et al. 2012; Ebbeling et al. 2012), and it has been shown that long term weight gain is inversely associated with consumption of foods such as fruits, vegetables and whole grains (Mozaffarian et al. 2011).

Given that sleep and diet quality are both associated with elevated obesity risk, a developing body of literature is considering the association between these risk factors (Chaput 2013; Kjeldsen et al. 2014; Bel et al. 2013; Stern et al. 2014). Previous cross-sectional (Kjeldsen et al. 2014; Westerlund et al. 2009) and prospective (Tatone-Tokuda et al. 2011) work has shown an association between short sleep duration and increased intake of added sugar and SSBs (Kjeldsen et al. 2014; Tatone-Tokuda et al. 2011), as well as increased energy density (Westerlund et al. 2009; Kjeldsen et al. 2014), and decreased intake of fruits and vegetables (Tatone-Tokuda et al. 2011). As noted above, the pathway between insufficient sleep and obesity may be in part due to increased hunger and increased opportunity to eat. It is also possible that the association between sleep and diet is confounded by television viewing and television in the bedroom. Higher levels of television viewing have been associated with increased intake of food and beverages heavily advertised on television (Falbe et al. 2014; Wiecha et al. 2006; Pearson et al. 2011), as well as lower levels of fruit and vegetable intake (Falbe et al. 2014; Boynton-Jarrett et al. 2003; Pearson et al. 2011), while television viewing and television in the bedroom may also predict suboptimal sleep (Cain and Gradisar 2010; Falbe et al. 2015). Further understanding these associations will help to inform the development of future interventions. This study examines the extent to which insufficient sleep is associated with adverse diet in elementary and middle school students taking part in a multi-sector, community-based obesity prevention intervention (Davison et al. 2014; Taveras, Blaine, et al. 2014a).

Methods

Participants and Setting

Data were drawn during the Fall semester of the 2012-13 school year from baseline surveys of 4th and 7th graders in public schools located in two communities participating in the Massachusetts Childhood Obesity Research Demonstration Study (MA-CORD) (Davison et al. 2014; Taveras, Blaine, et al. 2014a). MA-CORD is a multi-sector community intervention to address childhood obesity, particularly among low-income children.

Children in this sample originated from two MA-CORD communities that are predominantly non-Hispanic white (68%) with sizeable Hispanic populations (17% and 22%). Per capita incomes in MA-CORD communities were substantially lower (approximately $22,900 and $21,300) than in the state overall (approximately $35,500) in 2012 (United States Census Bureau n.d.). A total of 2456 student across 29 schools were invited to complete the baseline survey. All data collection procedures were approved by the Internal Review Board at the Massachusetts Department of Public Health.

Measures

Students completed a self-reported survey during the annual BMI screening mandated in all public schools in Massachusetts. Trained school nurses and/or teachers read survey items aloud to 4th graders; 7th grade students completed the survey independently.

Diet indicators examined the frequency of consumption on the previous day of: vegetables (cooked or uncooked, not including French fries, fried potatoes, or potato chips), fruit (fresh, frozen, canned or dried), 100% juice, juice drinks (punch, Kool-Aid®, sports drinks, or other fruit-flavored drinks), soda (regular, non-diet), and water (plain water, sparkling or any other water drink that has 0 calories). These variables were assessed with the following question and response options: Yesterday, did you eat any ____? No, I did not eat any ____ yesterday; Yes, I ate ____ 1 time yesterday; Yes, I ate ____ 2 times yesterday; Yes, I ate ____ 3 or more times yesterday. Outcomes were modeled as continuous frequency of consumption. The highest response category, 3 or more times, was conservatively coded as 3 times per day. Composite measures for SSBs (the sum of juice drinks and regular soda) and caloric beverages (juice drinks, regular soda and 100% juice) were also examined. Dietary recall questions were obtained from the School Physical Activity and Nutrition Project (SPAN) survey, for which there is evidence for moderate validity in students as young as 4th grade (Thiagarajah et al. 2008).

The exposure of interest was optimal weekday sleep duration (National Sleep Foundation n.d.), modeled dichotomously: $\geq$10 hours/weekday (optimal) vs. <10 hours/weekday (insufficient). Usual weekday sleep duration was estimated by taking the difference between self-reported bedtime and wake time for a usual weekday in the past week, assessed with the following questions: "On a usual weekday this past week, when did you go to bed at night?" and "When did you wake up the next morning?" Self-reported questionnaire items assessing sleep duration among youth have generally been moderately to strongly correlated with sleep duration calculated from actigraphy measures and sleep diaries (Matricciani et al. 2012).

Covariates included self-reported gender, grade, race/ethnicity, physical activity, screen time and presence of a television in the bedroom. Students described their race/ethnicity by selecting one or more of the following: white, black or African American, Hispanic or Latino, Asian, Native Hawaiian or other Pacific Islander, American Indian or Alaska Native, or other. Race/ethnicity was categorized into Hispanic, non-Hispanic White, non-Hispanic Black, non-Hispanic other, non-Hispanic multiracial. Due to small numbers, American Indian or Alaska Natives, Asian, and Hawaiian or Pacific Islander who were not Hispanic were collapsed into the non-Hispanic other category. A measure of physical activity was obtained from the SPAN survey (Thiagarajah et al. 2008), in which physical activity was assessed by asking students on which days in the last week they took part in physical activity that made their heart beat fast or made them breathe hard for at least 30 minutes. Responses were summed to 0-7 days and modeled as a continuous variable. Presence of a television in the bedroom was determined with the following yes/no response question, “Is there a television in the room where you sleep?” To determine screen time, children were asked separately about how much time they spent with television/DVDs and video/computer games on a usual weekday and weekend in the past week (data on smartphones and/or tablets were not collected). Moderate validity has been reported for similar surveys of self-reported screen time among youth (Gortmaker et al. 1999; Schmitz et al. 2004).

Although BMI is associated with diet quality, it was not included as a covariate because it is likely a down-stream consequence of diet and therefore does not meet the structural definition of a confounder. Furthermore, evidence is mixed regarding the association between BMI and sleep duration for children and adolescents (Guidolin & Gradisar 2012).

Analytic Sample

Eligible subjects had complete data on sleep, dietary outcomes, gender, age, school, presence of a television in the bedroom, screen time, and physical activity. After excluding students with missing data on exposures, outcomes and covariates, our analytic sample consisted of 1870 children.

Statistical analyses

We used linear regression to examine the associations of sleep duration with dietary indicators (vegetables, fruit, 100% juice, juice drinks, soda, and water). Generalized estimating equations were used for estimation, specifying an exchangeable covariance structure to account for clustering by school (Hanley 2003; Liang & Zeger 1986).

Model 1 was unadjusted. Model 2, a partially adjusted model, adjusted for community, gender, grade, and race/ethnicity. Model 3, the fully adjusted model, additionally adjusted for physical activity, presence of a television in the bedroom, and screen time. To test for potential heterogeneity of associations by grade and gender, grade- and gender-stratified models were examined, and cross-products of these terms with optimal sleep duration were assessed in fully adjusted models. Analyses were conducted using SAS (version 9.3; SAS Institute, Cary, NC, USA).

Results

Characteristics of students in the sample are described in **Table 1.1**. The students had a mean age (SD) of 10.6 (1.5) years, while Hispanic (41%) and non-Hispanic White (39%) were the predominant racial/ethnic groups. Approximately 48% were overweight or obese. A higher proportion of 7^{th} graders reported insufficient sleep (less than 10 hours per 24 hours) in comparison to 4^{th} graders (80% and 49% respectively). Furthermore, 75% of students reported the presence of a television in the bedroom. Overall, students reported an average of 5.06 ± 4.31 hours of screen time per day.

Table 1.1. Sample characteristics, Massachusetts Childhood Obesity Research Demonstration Project (Fall 2012).

	All (N=1870)	**Grade 4 (N=1104)**	**Grade 7 (N=766)**	**Boys (N=916)**	**Girls (N=954)**
Child characteristics, mean±SD or %					
Female	51.0	51.7	50.0	0	100.0
Age, years	10.6 ± 1.5	9.4 ± 0.6	12.3 ± 0.6	10.7 ± 1.6	10.5 ± 1.5
Race/Ethnicity					
Hispanic	40.8	39.2	43.0	40.1	41.4
White, non-Hispanic	38.6	38.4	38.8	39.9	37.3
Black, non-Hispanic	9.7	10.8	8.2	9.9	9.5
Other, non-Hispanic[a]	4.0	4.6	3.1	4.4	3.7
Multiracial, non-Hispanic[b]	7.0	7.0	6.9	5.8	8.1
Overweight (BMI ≥85th-<95th percentile[c])	19.5	19.5	19.4	18.4	20.4
Obese (BMI ≥95th percentile[c])	28.5	27.7	29.6	30.2	26.9
Days in past week participated in ≥30 minutes of physical activity	3.16 ± 2.20	3.35 ± 2.22	2.90 ± 2.14	3.27 ± 2.28	3.06 ±2.11
Screen time (hours/day)	5.06 ± 4.31	4.64 ± 4.07	5.66 ± 4.57	5.50 ± 4.29	4.63 ± 4.28
Television in the bedroom	75.2	74.8	75.9	78.4	72.2
Sleep duration per 24 hours on a weekday in the past week					
≥10 hours (optimal)	38.5	51.5	19.6	34.7	42.0

Table 1.1 (continued). Sample characteristics, Massachusetts Childhood Obesity Research Demonstration Project (Fall 2012).

	All (N=1870)	**Grade 4 (N=1104)**	**Grade 7 (N=766)**	**Boys (N=916)**	**Girls (N=954)**
Diet indicators, mean±SD (frequency consumed on previous day)					
Vegetables	0.92 ± 0.92	0.93 ± 0.95	0.90 ± 0.88	0.85 ± 0.92	0.99 ± 0.92
Fruit	1.18 ± 0.98	1.20 ± 0.99	1.14 ± 0.97	1.14 ± 0.99	1.21 ± 0.98
100% juice	0.99 ± 0.97	1.01 ± 0.97	0.95 ± 0.98	0.96 ± 1.00	1.01 ± 0.95
Juice drinks	0.86 ± 0.96	0.85 ± 0.96	0.86 ± 0.97	0.91 ± 0.99	0.80 ± 0.93
Soda	0.59 ± 0.84	0.56 ± 0.82	0.64 ± 0.87	0.63 ± 0.87	0.56 ± 0.81
Water	1.67 ± 1.08	1.69 ± 1.07	1.64 ± 1.10	1.61 ± 1.10	1.72 ± 1.06
SSBs[d]	1.45 ± 1.37	1.42 ± 1.37	1.50 ± 1.37	1.54 ± 1.42	1.36 ± 1.32

[a]Includes American Indian or Alaska Natives, Asian, Hawaiian or Pacific Islander.
[b]Includes youth who indicated more than one race but did not identify as Hispanic/Latino.
[c]Determined by 2000 CDC growth charts.
[d]SSBs: Sugar-sweetened beverages, composite measure included juice drinks (punch, Kool-Aid®, sports drinks, or other fruit-flavored drinks, not including 100% juice), and regular soda (regular, non-diet).

Results from models examining the association between optimal sleep duration and dietary outcomes are presented in **Table 1.2**. In the unadjusted model, children reporting insufficient sleep duration (<10 hours of sleep per 24 hours) consumed vegetables less frequently (β=-0.11, 95% CI:-0.20, -0.03), regular soda more frequently (β=0.16, 95% CI:0.08, 0.24), and SSBs more frequently (β=0.22, 95% CI:0.09, 0.35) than children reporting optimal sleep duration.

Table 1.2. Association between insufficient sleep duration (less than 10 hours per 24 hours) in the past week and dietary outcomes (# of occasions consumed on previous day); N =1870, Massachusetts Childhood Obesity Research Demonstration Project (Fall 2012).

	Model 1 (unadjusted) β (95% CI)	**Model 2** (partially adjusted)[a] β (95% CI)	**Model 3** (fully adjusted)[b] β (95% CI)
Vegetables	-0.11** (-0.20, -0.03)	-0.10* (-0.19, -0.01)	-0.09* (-0.18, -0.01)
Fruit	-0.07 (-0.16, 0.03)	-0.05 (-0.13, 0.04)	-0.06 (-0.13, 0.02)
100% juice	-0.06 (-0.15, 0.03)	-0.05 (-0.14, 0.03)	-0.07 (-0.15, 0.01)
Juice drinks	0.06 (-0.03, 0.15)	0.05 (-0.04, 0.14)	0.01 (-0.09, 0.11)
Regular soda	0.16*** (0.08, 0.24)	0.16*** (0.07, 0.24)	0.11** (0.03, 0.20)
SSBs[c]	0.22*** (0.09, 0.35)	0.21** (0.05, 0.37)	0.13 (-0.03, 0.29)
Water	-0.01 (-0.11, 0.09)	0.02 (-0.08, 0.11)	0.01 (-0.08, 0.11)

[a]Adjusted for grade, gender, race/ethnicity (Hispanic, non-Hispanic white, non-Hispanic black, non-Hispanic other, non-Hispanic multiracial), and city.
[b]Additionally adjusted for days in past week participated in ≥30 minutes of physical activity, screen time and presence of TV in the bedroom.
[c]SSBs: Sugar-sweetened beverages, composite measure included juice drinks (punch, Kool-Aid®, sports drinks, or other fruit-flavored drinks, not including 100% juice), and regular soda (regular, non-diet).
***P<0.001, **P<0.01, *P<0.05

Similar associations between sleep duration and students' vegetable and soda consumption were identified in the partially adjusted and fully adjusted models but were slightly attenuated (vegetables: β=-0.09, 95% CI:-0.18, -0.01; soda: β=0.11, 95% CI:0.03, 0.20). The association between sleep duration and students' SSB consumption was attenuated more substantially, and was no longer significant, following adjustment for covariates (β=0.13, 95% CI:-0.03, 0.29). Similarly, our analysis of the composite measure for caloric beverages showed that the effect estimate was attenuated and non-significant across all models (results not shown). Sleep duration was not significantly associated with consumption of fruit, 100% juice, juice drinks, or water. Stratified results by grade and gender are presented in **Table 1.3a and 1.3b**; tests for heterogeneity did not detect significant differences in results by grade or gender (all p-values >0.05).

Table 1.3a. Association between insufficient sleep duration (less than 10 hours per 24 hours) in the past week and dietary outcomes (# of occasions consumed on previous day) – Stratified by grade. Massachusetts Childhood Obesity Research Demonstration Project (Fall 2012).

	Model 1 (unadjusted) β (95% CI)	**Model 2 (partially adjusted)[a] β (95% CI)**	**Model 3 (fully adjusted)[b] β (95% CI)**
Grade 4 (n = 1104)			
Vegetables	-0.11* (-0.23, 0.00)	-0.09 (-0.18, 0.01)	-0.08 (-0.18, 0.02)
Fruit	-0.07 (-0.19, 0.05)	-0.06 (-0.16, 0.05)	-0.06 (-0.17, 0.04)
100% juice	-0.04 (-0.15, 0.08)	-0.04 (-0.16, 0.07)	-0.06 (-0.18, 0.06)
Juice drinks	0.06 (-0.06, 0.17)	0.04 (-0.08, 0.17)	-0.01 (-0.13, 0.11)
Regular soda	0.15** (0.06, 0.25)	0.16** (0.05, 0.28)	0.10 (-0.02, 0.22)
SSBs[c]	0.21* (0.05, 0.37)	0.21 (-0.01, 0.42)	0.10 (-0.12, 0.31)
Water	-0.02 (-0.14, 0.11)	-0.01 (-0.13, 0.11)	0.01 (-0.12, 0.13)
Grade 7 (n = 766)			
Vegetables	-0.11 (-0.27, 0.04)	-0.10 (-0.29, 0.08)	-0.11 (-0.28, 0.05)
Fruit	-0.01 (-0.18, 0.16)	-0.01 (-0.19, 0.17)	-0.08 (-0.19, 0.03)
100% juice	-0.07 (-0.24, 0.10)	-0.09* (-0.17, -0.02)	-0.12** (-0.19, -0.04)
Juice drinks	0.08 (-0.10, 0.25)	0.08 (-0.06, 0.23)	0.05 (-0.11, 0.22)
Regular soda	0.15 (0.00, 0.30)	0.14** (0.05, 0.22)	0.13** (0.04, 0.21)
SSBs[c]	0.23 (-0.02, 0.47)	0.21* (0.04, 0.38)	0.14 (-0.05, 0.34)
Water	0.07 (-0.13, 0.26)	0.08 (-0.08, 0.23)	0.06 (-0.06, 0.19)

[a]Adjusted for grade, gender, race/ethnicity (Hispanic, non-Hispanic white, non-Hispanic black, non-Hispanic other, non-Hispanic multiracial), and city.

[b]Additionally adjusted for days in past week participated in ≥30 minutes of physical activity, screen time and presence of TV in the bedroom.

[c]SSBs: Sugar-sweetened beverages, composite measure included juice drinks (punch, Kool-Aid®, sports drinks, or other fruit-flavored drinks, not including 100% juice), and regular soda (regular, non-diet).

***P<0.001, **P<0.01, *P<0.05

Table 1.3b. Association between insufficient sleep duration (less than 10 hours per 24 hours) in the past week and dietary outcomes (# of occasions consumed on previous day) – Stratified by gender. Massachusetts Childhood Obesity Research Demonstration Project (Fall 2012).

	Model 1 (unadjusted) β (95% CI)	Model 2 (partially adjusted)[a] β (95% CI)	Model 3 (fully adjusted)[b] β (95% CI)
Boys (n = 916)			
Vegetables	-0.05 (-0.18, 0.07)	-0.09 (-0.22, 0.05)	-0.08 (-0.20, 0.05)
Fruit	0.02 (-0.11, 0.16)	0.01 (-0.09, 0.11)	0.01 (-0.08, 0.10)
100% juice	-0.03 (-0.17, 0.10)	-0.04 (-0.15, 0.07)	-0.04 (-0.16, 0.08)
Juice drinks	0.00 (-0.13, 0.14)	0.03 (-0.12, 0.18)	-0.02 (-0.16, 0.13)
Regular soda	0.19** (0.07, 0.31)	0.19** (0.07, 0.31)	0.15* (0.01, 0.29)
SSBs[c]	0.19* (0.00, 0.39)	0.22 (0.00, 0.43)	0.13 (-0.09, 0.36)
Water	0.05 (-0.10, 0.20)	0.04 (-0.09, 0.17)	0.04 (-0.11, 0.18)
Girls (n = 954)			
Vegetables	-0.15* (-0.27, -0.03)	-0.10 (-0.24, 0.05)	-0.10 (-0.24, 0.04)
Fruit	-0.14* (-0.26, -0.01)	-0.11 (-0.26, 0.03)	-0.13 (-0.26, 0.01)
100% juice	-0.08 (-0.21, 0.04)	-0.06 (-0.17, 0.05)	-0.09 (-0.19, 0.02)
Juice drinks	0.09 (-0.03, 0.21)	0.07 (-0.05, 0.19)	0.02 (-0.09, 0.14)
Regular soda	0.13* (0.02, 0.23)	0.12* (0.01, 0.24)	0.08 (-0.02, 0.19)
SSBs[c]	0.22* (0.05, 0.39)	0.20 (-0.01, 0.40)	0.11 (-0.08, 0.29)
Water	-0.04 (-0.18, 0.09)	0.01 (-0.11, 0.14)	0.01 (-0.11, 0.12)

[a]Adjusted for grade, gender, race/ethnicity (Hispanic, non-Hispanic white, non-Hispanic black, non-Hispanic other, non-Hispanic multiracial), and city.
[b]Additionally adjusted for days in past week participated in ≥30 minutes of physical activity, screen time and presence of TV in the bedroom.
[c]SSBs: Sugar-sweetened beverages, composite measure included juice drinks (punch, Kool-Aid®, sports drinks, or other fruit-flavored drinks, not including 100% juice), and regular soda (regular, non-diet).
***P<0.001, **P<0.01, *P<0.05

Discussion

The objective of this study was to examine the extent to which insufficient sleep was associated with indicators of diet quality in students taking part in the MA-CORD Project. After controlling for covariates, we found that students who reported sleeping <10 hours/day consumed soda more frequently (β=0.11, 95% CI:0.03, 0.20) and vegetables less frequently (β=-0.09, 95% CI:-0.18, -0.01) compared with students who reported optimal sleep. This study adds to the developing body of literature regarding the relationship between sleep and diet. Results from the current study substantiate previous findings that sleep duration is associated with diet quality (Kjeldsen et al. 2014; Tatone-Tokuda et al. 2011; Westerlund et al. 2009), in particular noting the association of both lower vegetable and higher soda consumption with insufficient sleep in this population. Relatively few studies to date have examined this association in a population of children (Kjeldsen et al. 2014; Tatone-Tokuda et al. 2011; Westerlund et al. 2009), and no known studies to date have been conducted in a low-income, diverse sample in the United States.

An important aspect of the current study was the consideration of soda and juice drinks separately as well as together (as SSBs). We found that intake of soda, but not juice drinks, was significantly associated with sleep duration in this population of children. Because many sodas contain caffeine, which may interfere with sleep onset, these results raise the question of whether inadequate sleep promotes soda consumption or vice-versa. The association could also be bidirectional, whereby children intentionally drink soda to stay up later, then feel tired following insufficient sleep and drink soda to reduce fatigue. The direction of the association could not be assessed given the cross-sectional nature of the data. Future longitudinal studies will be needed to further consider causality.

Screen time was included in the fully adjusted model as a covariate. It has been shown that increased screen time is associated with increased consumption of SSBs and decreased consumption of fruits and vegetables (Falbe et al. 2014; Boynton-Jarrett et al. 2003; Wiecha et al. 2006; Pearson et al. 2011). Screen time may be either a confounder or a mediator of the sleep-diet relationship. For instance, if children stay up later as a result of watching television and consume more soda (the second most advertised food/beverage item on television) (Federal Trade Commission 2012) as a result of exposure to food advertising (Harris et al. 2009; Anschutz et al. 2009; Halford et al. 2007), screen time would act as a confounder. If, instead, children who have difficulty falling asleep use screen time as a sleep aid (Eggermont & Van den Bulck 2006), it may act as a mediator, in which case our fully adjusted estimates would be attenuated. While the role of screen time in the sleep-diet relationship warrants further consideration, the fact that the observed associations persisted following adjustment for screen time suggests that other mechanisms are at play as well.

Other potential mechanisms for the sleep-diet relationship include the possibility that lack of sleep leads to more eating in general, and it may be that the types of foods and beverages available to youth late at night are more likely to be convenience items, in contrast to vegetables, which typically require more preparation and are eaten with meals. Extra calories consumed while staying up late may be displacing appetite during meals the next day, reducing vegetable intake. Lack of parental supervision could also be associated with youth's dietary intake later at night. Lack of supervision may be associated with age, whereby older children have less supervision. While there were no significant differences by grade, it is worth noting that there is a possibility of greater measurement error in younger grades, which would lead to attenuated associations.

Given that some schools had a higher proportion of completed surveys than others, we examined the relationship between survey completeness and demographics using linear regression. We found a weak relationship between % non-white students in each school and % survey completeness, indicating that schools with a higher proportion of non-white students were slightly less likely to complete surveys than schools with lower proportions of non-white students. Future studies might examine this relationship further.

The primary limitation of this study is its cross-sectional design. Another limitation is that measures were self-reported, introducing random error and the possibility of bias due to social desirability. We did not collect comprehensive dietary intake data, so we were unable to examine other dietary outcomes, such as total calories and consumption of fast food, snacks, and other convenience foods like microwaveable items. Moreover, we did not collect data on socioeconomic status, parental education or parenting style, which are also potential confounders of the association between sleep and diet. This study has several strengths, including the large and racially/ethnically diverse sample, the fact that we were able to consider variability by grade and gender, and our consideration of soda and juice drinks separately as well as together

In light of the growing body of evidence regarding the association between sleep and diet quality, as well as the independent associations of each with obesity, there is a clear need for further research in this area. There is also a need for further consideration of the mechanisms at play, particularly given the caffeine content of many sodas. More detailed data collection regarding consumption, including time of day for caffeine consumption, could be informative with regards to teasing out the potential direction of causality between SSBs and sleep. In the meantime, there is little risk to including sleep recommendations as a component of obesity prevention interventions, and possibly much to gain. Future interventions should consider sleep as a component, potentially via prompts in the medical setting and/or targeted education for parents and children via community- and school-based programs.

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References

Anschutz, D.J., Engels, R.C. & Van Strien, T., 2009. Side effects of television food commercials on concurrent nonadvertised sweet snack food intakes in young children. *The American Journal of Clinical Nutrition*, 89(5), pp.1328–1333.

Bel, S. et al., 2013. Association between self-reported sleep duration and dietary quality in European adolescents. *British Journal of Nutrition*, 110(05), pp.949–959.

Boynton-Jarrett, R. et al., 2003. Impact of Television Viewing Patterns on Fruit and Vegetable Consumption Among Adolescents. *Pediatrics*, 112(6), pp.1321–1326.

Burt, J. et al., 2014. Sleep and eating in childhood: a potential behavioral mechanism underlying the relationship between poor sleep and obesity. *Sleep Medicine*, 15(1), pp.71–75.

Chaput, J.-P., 2013. Sleep patterns, diet quality and energy balance. *Physiology & Behavior*, pp.1–6.

Davison, K. et al., 2014. Evaluation overview for the Massachusetts Childhood Obesity Research Demonstration (CORD) project. *Childhood Obesity*, pp.1–39.

de Ruyter, J.C. et al., 2012. A Trial of Sugar-free or Sugar-Sweetened Beverages and Body Weight in Children. *New England Journal of Medicine*, 367(15), pp.1397–1406.

Ebbeling, C.B. et al., 2012. A Randomized Trial of Sugar-Sweetened Beverages and Adolescent Body Weight. *New England Journal of Medicine*, 367(15), pp.1407–1416.

Eggermont, S. & Van den Bulck, J., 2006. Nodding off or switching off? The use of popular media as a sleep aid in secondary-school children. *Journal of Paediatrics and Child Health*, 42(7-8), pp.428–433.

Falbe, J. et al., 2014. Longitudinal relations of television, electronic games, and digital versatile discs with changes in diet in adolescents. *The American Journal of Clinical Nutrition*,

p.ajcn.088500. Available at:
http://ajcn.nutrition.org/content/early/2014/08/13/ajcn.114.088500.abstract.

Falbe, J. et al., 2015. Sleep Duration, Restfulness, and Screens in the Sleep Environment. *Pediatrics*, 135(2), pp.e367–e375.

Federal Trade Commission, 2012. A Review of Food Marketing to Children and Adolescents: Follow-Up Report. pp.1–356.

Gortmaker, S.L. et al., 1999. Reducing Obesity via a School-Based Interdisciplinary Intervention Among Youth. *Arch Pediatr Adolesc Med*, 153, pp.409–418.

Guidolin, M. & Gradisar, M., 2012. Is shortened sleep duration a risk factor for overweight and obesity during adolescence? A review of the empirical literature. *Sleep Medicine*, 13(7), pp.779–786.

Halford, J.C.G. et al., 2007. Beyond-brand effect of television (TV) food advertisements/commercials on caloric intake and food choice of 5–7-year-old children. *Appetite*, 49(1), pp.263–267.

Hanley, J.A., 2003. Statistical Analysis of Correlated Data Using Generalized Estimating Equations: An Orientation. *American Journal of Epidemiology*, 157(4), pp.364–375.

Harris, J.L., Bargh, J.A. & Brownell, K.D., 2009. Priming effects of television food advertising on eating behavior. *Health Psychology*, 28(4), pp.404–413.

Hart, C.N., Cairns, A. & Jelalian, E., 2011. Sleep and Obesity in Children and Adolescents. *Pediatric Clinics of North America*, 58(3), pp.715–733.

Hu, F., 2008. *Obesity Epidemiology*, Oxford University Press.

Kjeldsen, J.S. et al., 2014. Short sleep duration and large variability in sleep duration are independently associated with dietary risk factors for obesity in Danish school children.

International Journal of Obesity, 38(1), pp.32–39.

Liang, K.-Y. & Zeger, S.L., 1986. Longitudinal data analysis using generalized linear models. *Biometrika*, 73(1), pp.13–22.

Malik, V.S. et al., 2013. Sugar-sweetened beverages and weight gain in children and adults: a systematic review and meta-analysis. *The American Journal of Clinical Nutrition*, 98(4), pp.1084–1102.

Matricciani, L., Olds, T. & Petkov, J., 2012. In search of lost sleep: Secular trends in the sleep time of school-aged children and adolescents. *Sleep Medicine Reviews*, 16(3), pp.203–211.

Mozaffarian, D. et al., 2011. Changes in Diet and Lifestyle and Long-Term Weight Gain in Women and Men. *New England Journal of Medicine*, 364, pp.2392–2404.

National Sleep Foundation, 2014 Sleep in America Poll. Available at: http://sleepfoundation.org/sleep-polls-data/2014-sleep-the-modern-family [Accessed September 18, 2014].

National Sleep Foundation, Children and Sleep. *http://sleepfoundation.org/sleep-topics/children-and-sleep*. Available at: http://sleepfoundation.org/sleep-topics/children-and-sleep [Accessed September 17, 2014].

Ogden, C.L. et al., 2014. Prevalence of Childhood and Adult Obesity in the United States, 2011-2012. *JAMA*, 311(8), pp.806–814.

Patel, S.R. & Hu, F.B., 2008. Short Sleep Duration and Weight Gain: A Systematic Review. *Obesity*, 16(3), pp.643–653.

Pearson, N., Ball, K. & Crawford, D., 2011. Mediators of longitudinal associations between television viewing and eating behaviours in adolescents. *International Journal of Behavioral Nutrition and Physical Activity*, 8(1), p.23.

Sadeh, A., Gruber, R. & Raviv, A., 2002. Sleep, Neurobehavioral Functioning, and Behavior Problems in School-Age Children. *Child Development*, 73(2), pp.405–417.

Schmitz, K.H. et al., 2004. Reliability and Validity of a Brief Questionnaire to Assess Television Viewing and Computer Use by Middle School Children. *Journal of School Health*, 74(9), pp.370–377.

Stern, J.H. et al., 2014. Short sleep duration is associated with decreased serum leptin, increased energy intake and decreased diet quality in postmenopausal women. *Obesity*, 22(5), pp.E55–E61.

Tatone-Tokuda, F. et al., 2011. Sex differences in the association between sleep duration, diet and body mass index: a birth cohort study. *Journal of Sleep Research*, 21(4), pp.448–460.

Taveras, E.M. et al., 2012. Healthy Habits, Happy Homes: Methods and baseline data of a randomized controlled trial to improve household routines for obesity prevention. *Preventive Medicine*, 55(5), pp.418–426.

Taveras, E.M., Blaine, R., et al., 2014a. *Design of the Massachusetts Childhood Obesity Research Demonstration (MA-CORD) Study*,

Taveras, E.M., Gillman, M.W., et al., 2014b. Chronic Sleep Curtailment and Adiposity. *Pediatrics*, 133(6), pp.1013–1022.

Thiagarajah, K. et al., 2008. Validating the Food Behavior Questions from the Elementary School SPAN Questionnaire. *Journal of Nutrition Education and Behavior*, 40(5), pp.305–310.

United States Census Bureau, State & County QuickFacts. *http://quickfacts.census.gov/qfd/states/25000.html*. Available at: http://quickfacts.census.gov/qfd/states/25000.html [Accessed September 17, 2014].

Westerlund, L., Ray, C. & Roos, E., 2009. Associations between sleeping habits and food consumption patterns among 10–11-year-old children in Finland. *British Journal of Nutrition*, 102(10), pp.1531–1537.

Wiecha, J.L. et al., 2006. When Children Eat What They Watch. *Arch Pediatr Adolesc Med*, 160, pp.436–442.

Chapter 2:

Calorie Underestimation When Buying High-Calorie Beverages in Fast-Food Contexts

Rebecca L. Franckle, Jason P. Block, and Christina A. Roberto

Abstract

Objectives: To examine whether purchasing a high-calorie beverage (HCB) was associated with greater calorie underestimation of fast food.

Methods: 1877 adults and 1178 adolescents visiting 89 fast food restaurants estimated the calories of items they purchased. We examined whether purchasing a HCB was associated with calorie estimates.

Results: Calorie underestimation was greater among those who purchased a HCB vs. those who did not (adults: 324±698 vs. 102±591 calories; adolescents: 360±602 vs. 198±509 calories). This difference remained significant for adults (-65, 95% CI: -128, -2), but not adolescents (7, 95% CI: -57, 71), after adjusting for total calories purchased. Calorie underestimation was also greater among those who purchased a high-calorie side item vs. those who did not (adults: 228±769 vs. 132±499 calories; adolescents: 347±653 vs. 194±451 calories). After adjusting for covariates, this difference became positive and significant for both adults (93, 95% CI: 25, 161) and adolescents (108, 95% CI: 34, 182).

Conclusions: Adults underestimated the calories of their fast food purchases to a greater degree when they bought a HCB. These results suggest that purchasing HCBs may uniquely contribute to calorie underestimation among adults.

Introduction

Previous research has shown that people eating at fast food restaurants underestimate the calorie content of their purchases (Block et al. 2013; Elbel 2011; Taksler & Elbel 2014; Bleich & Pollack 2010), but little is known about whether purchasing beverages affects calorie estimates. Sugar sweetened beverages (SSBs) are associated with obesity and chronic diseases (Hu 2013; Malik et al. 2013; de Ruyter et al. 2012; Ebbeling et al. 2012), and intake of liquid calories may lead to less satiety or perceived satiety than does intake of solid calories (Mattes 2006).

Because beverages are generally not the central focus of a meal and can be consumed quickly and with little effort, it is possible that people fail to account for the calories in high-calorie beverages (HCBs) more so than other foods. If this is the case, it would lend support to the idea that SSBs are more problematic than other caloric foods that are often over consumed.

We examined the accuracy of calorie estimation among adults and adolescents dining at fast food restaurants on the basis of whether they ordered a high-calorie beverage. We hypothesized that participants would be worse at estimating the total calories of their purchase when it included a HCB.

Methods

The methods for this paper have been previously described (Block et al. 2013). We interviewed 1877 adults (≥ 18 years old) at dinnertime and 1178 adolescents (11-20 years old) at lunch or after school when dining at fast food restaurants (6 chains, 89 restaurants) in Boston and Springfield, MA; Providence, RI; and Hartford, CT, and asked them to estimate calories of items they purchased. Forty-three percent of adults, and 49% of adolescents were female. Sixty-two percent of adults, and 82% of adolescents were non-white.

We determined the total calories purchased on the basis of customer receipts and calories listed on the restaurants' websites. Beverages included all caloric and non-caloric drinks ordered, and we considered them "high-calorie" if they had 140 or more calories (the caloric content of a small, 16 fluid ounce, McDonald's Coca-Cola Classic). Using linear regression, we examined the association between purchasing a HCB and the accuracy of estimating total calories purchased. We controlled for total calories purchased because there is more room for underestimation with higher calorie meals. Additional covariates included age, body mass index (defined as weight in kilograms divided by the square of height in meters), gender, race/ethnicity and restaurant chain.

Results

Overall, 621 adults (33%) and 451 adolescents (38%) purchased a HCB. On average, adults underestimated their purchases by 175±636 calories, whereas adolescents underestimated by 259±551 calories. Underestimates were greater among those who purchased a HCB than among those who did not (adults: 324±698 vs. 102±591 calories; adolescents: 360±602 vs. 198±509 calories) (see **Figure 2.1**). In the unadjusted model, purchasing a HCB accounted for a difference of -217 (95% CI: -279, -154) calories in adults and -160 (95% CI: -226, -94) calories in adolescents. After adjusting for covariates, this difference remained significant for adults (-65, 95% CI: -128, -2; p=0.04), but became non-significant for adolescents (7, 95% CI: -57, 71; p=0.83) (see **Table 2.1a**). We obtained similar results when analyzing beverage calories as a continuous rather than a dichotomous variable.

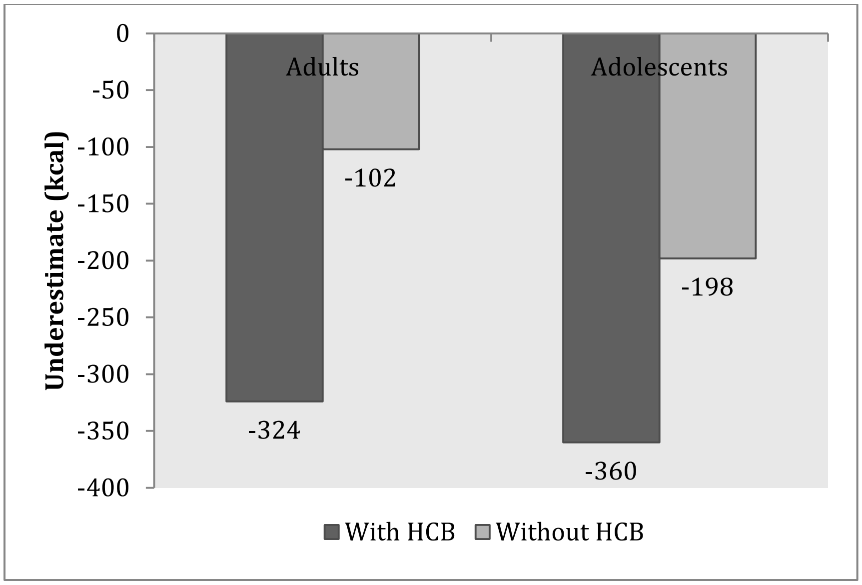

Figure 2.1. Calorie estimation accuracy among adults and adolescents, with and without the purchase of a high-calorie beverage (HCB; defined as a beverage with ≥ 140 calories).

Table 2.1a. Regression analyses examining predictors of calorie estimation accuracy when purchasing a high-calorie beverage[a]

		Adults (N=1877)		Adolescents (N=1178)	
		β	95% CI	β	95% CI
Buying a high-calorie beverage		**-65***	**(-128, -2)**	7	(-57, 71)
Age[b]		**-29****	**(-47, -10)**	**18****	**(7, 29)**
Body mass index (per 5 kg/m²)		**25***	**(2, 48)**	13	(-18, 44)
Male		-29	(-85, 28)	14	(-43, 72)
Race/ ethnicity	**Black**	**-138*****	**(-206, -70)**	**-119****	**(-204, -34)**
	Hispanic	**-121****	**(-202, -40)**	**-128****	**(-216, -40)**
	Asian	**-174***	**(-318, -30)**	**-225*****	**(-356, -93)**
	Other[c]	-82	(-185, 21)	**-120***	**(-224, -17)**
	White	Ref	Ref	Ref	Ref
Chain	**Subway**	**-172*****	**(-255, -89)**	**-215*****	**(-321, 109)**
	Burger King	-6	(-78, 65)	0	(-75, 75)
	Wendy's	13	(-85, 110)	42	(-59, 144)
	KFC	**193*****	**(92, 293)**	n/a	n/a
	Dunkin' Donuts	n/a	n/a	-53	(-146, 41)
	McDonald's	Ref	Ref	Ref	Ref

[a] Model was adjusted for total calories purchased, age, body mass index, sex, race/ethnicity and restaurant chain
[b] Age was per year for adolescents and per 10 years for adults
[c] This category includes other or >1 race/ethnicity (participants could self-identify with as many race/ethnicity categories as desired)
Boldface indicates statistical significance (*p < 0.05, **p < 0.01, ***p < 0.001)

To assess the potentially unique contribution of ordering a HCB to calorie underestimation, we examined whether ordering high-calorie side items (defined as items ≥ 140 calories for consistency with our definition of HCB) was associated with calorie underestimation. A total of 862 adults (46%) and 507 adolescents (43%) purchased at least one high-calorie side item. In the unadjusted model, calorie underestimation was greater among those who purchased a high-calorie side item vs. those who did not (adults: 228±769 vs. 132±499 calories; adolescents: 347±653 vs. 194±451 calories).

After we adjusted for covariates, this difference was positive and significant for both adults (93, 95% CI: 25, 161; p=0.01) and adolescents (108, 95% CI: 34, 182; p<0.01) (see **Table 2.1b**). In this case, a positive parameter estimate indicates that customers buying side items underestimated calorie content less than if they did not buy a side. In contrast, customers buying a HCB underestimated calorie content more than if they did not buy a HCB. We obtained similar results for adults (p = 0.04) when analyzing side-item calories as a continuous rather than dichotomous variable, but results became non-significant for adolescents (p = 0.09). This suggests adults may have greater trouble estimating calories in HCB compared to high-calorie food items and that HCB may be influencing calorie estimation in a unique way.

Table 2.1b. Regression analyses examining predictors of calorie estimation accuracy when buying a high-calorie side item[a]

		Adults (N=1877)		Adolescents (N=1178)	
		β	95% CI	β	95% CI
Buying a high-calorie side item		**93****	**(25, 161)**	**108****	**(34, 182)**
Age[b]		**-28****	**(-46, -9)**	**18****	**(7, 29)**
Body mass index (per 5 kg/m²)		**27***	**(4, 50)**	17	(-14, 47)
Male		-18	(-75, 38)	26	(-33, 83)
Race/ ethnicity	**Black**	**-140*****	**(-208, -71)**	**-113****	**(-197, -28)**
	Hispanic	**-131****	**(-212, -50)**	**-116***	**(-204, -28)**
	Asian	**-172***	**(-315, -28)**	**-205****	**(-337, -74)**
	Other[c]	-83	(-187, 20)	**-107***	**(-210, -3)**
	White	Ref	Ref	Ref	Ref
Chain	**Subway**	**-136****	**(-222, -51)**	**-181****	**(-288, -73)**
	Burger King	-15	(-86, 57)	-17	(-92, 58)
	Wendy's	12	(-85, 109)	37	(-64, 137)
	KFC	**174*****	**(72, 275)**	n/a	n/a
	Dunkin' Donuts	n/a	n/a	-25	(-120, 70)
	McDonald's	Ref	Ref	Ref	Ref

[a] Model was adjusted for total calories purchased, age, body mass index, sex, race/ethnicity and restaurant chain
[b] Age was per year for adolescents and per 10 years for adults
[c] This category includes other or >1 race/ethnicity (participants could self-identify with as many race/ethnicity categories as desired)
Boldface indicates statistical significance (*p < 0.05, **p < 0.01, ***p < 0.001)

Discussion

We found that adults underestimated calorie content by a larger amount when they bought a HCB, even when controlling for total calories purchased. Adolescents also demonstrated greater underestimation when they purchased a HCB, but this association was not significant after controlling for covariates.

Several possible mechanisms may explain this association. Adults ordering a HCB may be less knowledgeable of beverage versus food calories, or they may view beverage calories differently than solid calories, leading to more inaccurate estimates. In contrast, adolescents may have greater knowledge of beverage calories, perhaps influenced by school-based policy efforts (Cradock et al. 2011; Turner & Chaloupka 2012) and/or curricula that address SSBs (Carter et al. 2007; Cheung et al. 2007). Because adolescents are worse overall at estimating calories, the additional calories from HCBs may play less of a role in underestimation.

This study has several limitations. Customers may have elected to participate differentially based on interest and knowledge about food. Those with higher education levels may have been less persuaded to participate by the nominal monetary incentive. We did not measure some potentially important confounders, such as income or education, which could be associated with purchasing a HCB and accuracy of calorie estimation, although most of the neighborhoods we recruited from were low-income, suggesting that much of our sample is likely low-income.

We also assumed that the restaurant calorie information accounts for the ice in each beverage and did not make additional adjustments. We also do not have data on whether participants ordered free refills, and we may be missing data if additional beverages were purchased separately from the main order, but those receipts were not submitted. This study also has important strengths. We studied a large, racially and ethnically diverse sample of adults and adolescents and examined purchases at a range of large fast food chains at multiple locations.

Our results provide initial evidence that, among adults, purchasing HCBs may contribute to underestimating calories in restaurant meals. Future work should seek to replicate these findings and test for a causal link between HCBs and calorie estimation accuracy.

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Human Participant Protection

This study was approved by the institutional review boards (IRB) of Harvard Pilgrim Health Care and the Harvard School of Public Health.

References

Bleich, S.N. & Pollack, K.M., 2010. The publics' understanding of daily caloric recommendations and their perceptions of calorie posting in chain restaurants. *BMC Public Health*, 10(1), p.121.

Block, J.P. et al., 2013. Consumers' estimation of calorie content at fast food restaurants: cross sectional observational study. *BMJ*, 346(May23), pp.f2907.

Carter, J. et al., 2007. *Planet Health-2nd Edition*, Champaign, IL: Human Kinetics.

Cheung, L.W. et al., 2007. *Eat Well & Keep Moving-2nd Edition*, Human Kinetics.

Cradock, A.L. et al., 2011. Effect of School District Policy Change on Consumption of Sugar-Sweetened Beverages Among High School Students, Boston, Massachusetts, 2004-2006. *Preventing Chronic Disease*, 8(4, A74), pp.1–9.

de Ruyter, J.C. et al., 2012. A Trial of Sugar-free or Sugar-Sweetened Beverages and Body Weight in Children. *New England Journal of Medicine*, 367(15), pp.1397–1406.

Ebbeling, C.B. et al., 2012. A Randomized Trial of Sugar-Sweetened Beverages and Adolescent Body Weight. *New England Journal of Medicine*, 367(15), pp.1407–1416.

Elbel, B., 2011. Consumer Estimation of Recommended and Actual Calories at Fast Food Restaurants. *Obesity*, 19(10), pp.1971–1978.

Hu, F.B., 2013. Resolved: there is sufficient scientific evidence that decreasing sugar-sweetened beverage consumption will reduce the prevalence of obesity and obesity-related diseases. *Obesity Reviews*, 14(8), pp.606–619.

Malik, V.S. et al., 2013. Sugar-sweetened beverages and weight gain in children and adults: a systematic review and meta-analysis. *The American Journal of Clinical Nutrition*, 98(4), pp.1084–1102.

Mattes, R., 2006. Fluid calories and energy balance: The good, the bad, and the uncertain. *Physiology & Behavior*, 89(1), pp.66–70.

Taksler, G.B. & Elbel, B., 2014. Calorie labeling and consumer estimation of calories purchased. *International Journal of Behavioral Nutrition and Physical Activity*, 11(1), pp.1–8.

Turner, L. & Chaloupka, F.J., 2012. Encouraging Trends in Student Access to Competitive Beverages in US Public Elementary Schools, 2006-2007 to 2010-2011. *Arch Pediatr Adolesc Med*, 166(7), pp.673–675.

Chapter 3:

Purchasing patterns at a Northeastern supermarket chain and implications for the Supplemental Nutrition Assistance Program

Rebecca L. Franckle, Alyssa Moran, Tao Hou, Dan Blue, Julie Greene, Anne Thorndike, Michele Polacsek, Eric B. Rimm

Abstract

Introduction: There are currently no incentives to purchase healthier foods or limitations on purchasing unhealthy foods with Supplemental Nutrition Assistance Program (SNAP) benefits. Restructuring SNAP has been identified as a key opportunity to reduce both hunger and obesity in the US. SNAP recipients' purchasing data by product and/or retailer type is not publicly available, thus there is a need for direct analysis of grocery sales data to establish shopping patterns of recipients with respect to diet quality.

Methods: Two years of sales data from April 2012 through April 2014 were assessed from a large supermarket chain in the Northeast to describe overall food buying practices for transactions with and without SNAP reimbursement. Multivariate analysis of variance models adjusting for covariates (total amount spent on SNAP eligible items, season) were used to quantify relative differences in dollars spent on 34 predefined food categories.

Results: The sales dataset is comprised of 129,101 unique universal product codes (UPCs), and represents 283,849,806 unique shopping trips/transactions (of which 13.6 million were SNAP transactions, and 270.2 million were non-SNAP transactions). In the adjusted model, SNAP shoppers spent more than non-SNAP shoppers on sugar-sweetened beverages ($1.05), red meat ($1.55), and cold convenience foods ($1.37), and spent less on fruits ($1.44), vegetables ($1.33) and poultry ($1.38).

Conclusions: These findings help to establish current shopping patterns of SNAP recipients vs. non-recipients, and have implications for potential modifications to the program that would provide incentives to enhance purchasing of an overall healthier shopping trip.

Introduction

The Supplemental Nutrition Assistance Program (SNAP) provides financial assistance for food purchases to approximately 1 in 7 Americans. A burgeoning area of research is considering the diet quality of SNAP recipients (Fox & Cole, 2004; Leung et al., 2013; 2012). For example, one recent study using NHANES data demonstrated that SNAP recipients consumed 43% more sugar-sweetened beverages (SSBs), 47% more high-fat dairy, and 44% more processed meats, but 19% fewer nuts, seeds and legumes compared with non-recipients with similar socio-demographic characteristics (Leung et al., 2013). In addition, the USDA released a report in May 2015 about diet quality of Americans by SNAP participation status and cited similar diet quality differences between SNAP participants and either income-eligible or higher-income nonparticipants (Condon et al., 2015).

There are currently no incentives to purchase healthier foods or limitations on purchasing unhealthy foods with SNAP benefits (Blumenthal et al., 2013), though a pilot program in Massachusetts showed a significant improvement in participants' diets with the implementation of purchasing incentives for fruits and vegetables, demonstrating that the implementation of such incentive programs is feasible (Bartlett et al., 2014). Restructuring SNAP has been identified as a key opportunity to reduce both hunger and obesity in the US (Ludwig, Blumenthal, & Willett, 2012), and recent debate has focused on whether the program should place constraints on types of purchases that are allowable with benefits and/or otherwise incentivize healthy purchases. For example, public health advocates have increasingly made the suggestion to remove SSBs from the list of eligible food items for SNAP (Simon, 2012).

SNAP recipients' purchasing data by product and/or retailer type is not publicly available, thus there is a need for direct analysis of supermarket sales data to confirm the above findings regarding diet quality. Previous work has utilized grocery store scanner data to assess beverage purchases among a sample of families with a history of WIC participation (about half of which also participated in SNAP) and showed that SSBs accounted for 58% of beverage purchases made by SNAP households in this population (Andreyeva, Luedicke, Henderson, & Tripp, 2012a), but no known large-scale study to date has compared the shopping behaviors of SNAP vs. non-SNAP shoppers in the general population (i.e. in a sample not restricted to young families).

The proposed research will help to establish current shopping patterns of SNAP recipients vs. non-recipients in the northeastern United States using direct sales data, and has implications for the design of community-level interventions as well as for potential modifications to SNAP.

Methods

Individual universal product code (UPC) level grocery sales transaction records from a large regional supermarket chain were obtained to examine shoppers' purchasing patterns. Sales data were available from April 2012 through April 2014, and consist of sales from 188 stores across 5 states (Maine, Massachusetts, Vermont, New Hampshire and New York).

Transactions were categorized as being either a SNAP basket or a non-SNAP basket based on whether SNAP benefits were used to pay for any portion of the transaction. Two members of the research team categorized all UPCs in the sales database into 34 pre-defined food groups, amended from New York City food standards and Good Choice criteria (Hepps, 2015; Lederer, Curtis, Silver, & Angell, 2014), based on the item description (e.g. sugary drinks, fruits, vegetables, etc; see Appendix for detailed list of categories). A third member of the team was consulted to resolve any disagreements, and assignment of categories was further validated by cross-referencing the food groups with the store's database on item-level SNAP eligibility (i.e. if a UPC was assigned a food group of "non-food" but the store's database indicated that the item was eligible for purchase with SNAP benefits, the item was reviewed and reassigned a food group as needed).

For each shopping basket the database includes information on time of day, date, store, whether coupons were used, method of payment, and total transaction amount. SNAP-ineligible items were excluded (i.e. alcohol, non-food items and hot convenience foods), as were UPCs (12% of total UPCs) for which an item description was unavailable and therefore a food group could not be assigned. Low-income area stores were defined as stores with > the median % of population below the Federal Poverty Line in the store's buffer area, based on average distance traveled to primary store to approximate the store's catchment area (Census.gov, 2016; USDA ERS, 2016).

Data were analyzed using multivariate analysis of variance to assess SNAP status in relation to food purchasing habits, with the outcome of interest being the dollar amount spent on pre-defined categories of UPCs. Models were adjusted for covariates (total amount spent on all SNAP-eligible items, season) and additionally stratified by % poverty within each store's buffer zone (dichotomized by low-income vs. high-income).

Finally, results were used to estimate SNAP spending on SSBs in the U.S. by applying the % of SNAP spending on sugary drinks in the sales database to the known total annual SNAP spending nationally in 2013, the mid-point of the time period for which sales data were obtained.

Results

The sales dataset is comprised of 129,101 unique UPCs, and represents 283,849,806 unique shopping trips/transactions (of which 13.6 million were SNAP transactions, and 270.2 million were non-SNAP transactions). An overview of UPC characteristics in the sales database (% of sales by category, overall and stratified by SNAP status) is presented in **Table 3.1**, with differences by SNAP status observed in the SSB food group (55.1% vs. 40.4% of beverage spending for SNAP vs. non-SNAP shoppers) and red meat food group (48.9% vs. 39.8% of protein spending for SNAP vs. non-SNAP shoppers) in particular.

The top 10 food categories purchased by customers (overall and stratified by SNAP status) are presented in **Table 3.2**. Notably, the top category for both SNAP and non-SNAP shoppers was red meat, but the % of total sales differs (16.9% vs. 11.5% respectively). Furthermore, cold convenience foods (e.g. macaroni and cheese) are more popular among SNAP shoppers (ranked 3rd vs. 5th for non-SNAP shoppers) and SSBs are ranked as the 6th most frequently purchased food group for SNAP shoppers but do not enter the top ten for non-SNAP shoppers.

Figure 3.1 visually depicts the composition of average SNAP basket vs. average non-SNAP basket. With such a large dataset even small differences were significant, but the greatest discrepancies in composition between SNAP and non-SNAP transactions were major protein foods (35% vs 29%) and fruits and vegetables (14% vs 21%).

Table 3.1. Sales by UPC Category, April 2012 – April 2014

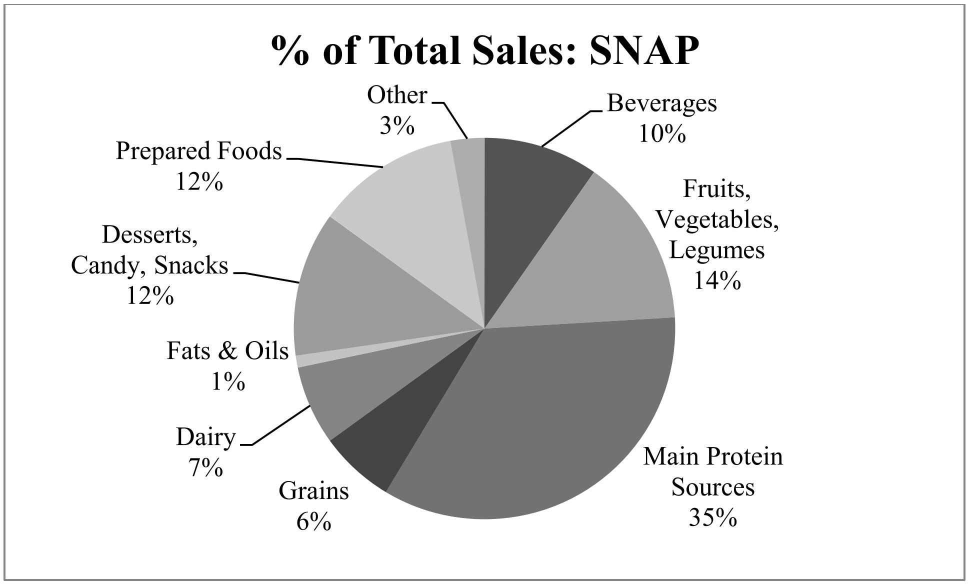
	% by category		
Category	**Non-SNAP**	**SNAP**	**Total**
Beverages			
Sugar-sweetened beverage	40.4%	55.1%	41.4%
Low-calorie beverage	7.1%	5.4%	7.0%
Unsweetened beverage	36.3%	27.7%	35.7%
100% Juice	16.2%	11.8%	15.8%
Fruits, Vegetables, Legumes			
Fruit	48.1%	47.4%	48.1%
Vegetable	44.7%	46.0%	44.8%
Bean	1.6%	2.1%	1.6%
Nut or seed	5.5%	4.5%	5.5%
Main Protein Sources			
Red meat	39.8%	48.9%	40.5%
Poultry	32.3%	28.1%	32.0%
Seafood	10.9%	7.7%	10.6%
Processed soy	0.6%	0.3%	0.6%
Processed meat	13.4%	13.1%	13.4%
Eggs	3.0%	1.9%	2.9%
Grains			
Bread	54.6%	50.4%	54.4%
Cereal	23.6%	25.4%	23.7%
Pasta, rice or other grain	21.8%	24.3%	21.9%
Dairy			
Milk	31.8%	35.4%	32.0%
Yogurt	20.5%	15.5%	20.2%
Cheese	47.7%	49.1%	47.8%
Fats & Oils			
Fat or oil - liquid	28.1%	23.5%	27.8%
Fat or oil - solid	71.9%	76.5%	72.2%
Desserts, Candy, Snacks			
Candy	10.4%	9.8%	10.4%
Cold or frozen dessert	13.7%	14.1%	13.7%
Sweet or salty snack	37.8%	35.4%	37.6%
Sweet bread, cake, cookies	38.1%	40.7%	38.3%
Prepared Foods			
Condiments, sauces, salad dressing	30.4%	23.3%	29.9%
Soup	9.5%	7.3%	9.3%

Table 3.1 (continued). Sales by UPC Category, April 2012 – April 2014

Pizza	6.9%	9.3%	7.1%
Convenience food (cold)	53.1%	60.1%	53.7%
Other			
Other food	100.0%	100.0%	100.0%

Table 3.2. Top 10 food categories by SNAP status

	Non-SNAP		SNAP		Overall	
Rank	**Category**	**% of Sales**	**Category**	**% of Sales**	**Category**	**% of Sales**
1	Red meat	11.5%	Red meat	16.9%	Red meat	11.9%
2	Fruit	10.2%	Poultry	9.7%	Fruit	10.0%
3	Vegetable	9.5%	Convenience foods (cold)	7.3%	Poultry	9.4%
4	Poultry	9.4%	Fruit	6.8%	Vegetable	9.3%
5	Convenience foods (cold)	5.1%	Vegetable	6.6%	Convenience foods (cold)	5.3%
6	Sweet bread, cake or cookie	4.8%	Sugar-sweetened beverage	5.4%	Sweet bread, cake or cookie	4.8%
7	Sweet or salty snack	4.7%	Sweet bread, cake or cookie	5.0%	Sweet or salty snack	4.7%
8	Processed meat	3.9%	Processed meat	4.5%	Processed meat	3.9%
9	Bread	3.8%	Sweet or salty snack	4.4%	Bread	3.8%
10	Cheese	3.8%	Cheese	3.3%	Cheese	3.8%



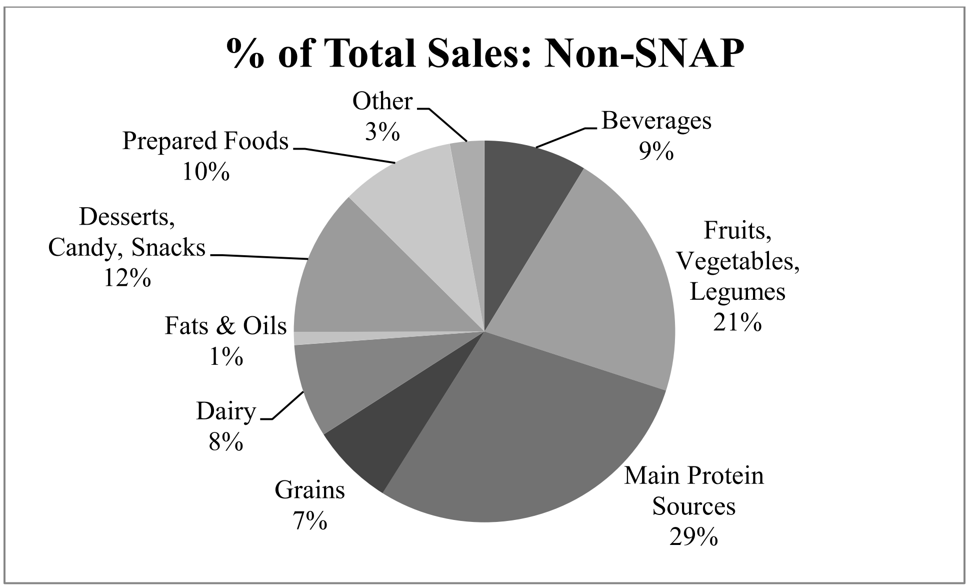


Figure 3.1. Composition of average SNAP basket vs. average non-SNAP basket

Results from models examining the association between receiving SNAP benefits and spending within the 31 SNAP-eligible food and beverage categories (in dollars) are presented in **Table 3.3**. Positive values indicate SNAP recipients spend more within a food or beverage category than non-recipients, and negative values indicate SNAP recipients spend less. In model 1, differences were apparent in several categories, with SNAP recipients spending more on food groups including sugar-sweetened beverages ($1.45), red meat ($4.44), poultry ($1.65), and cold convenience foods ($1.87). In model 2 (adjusted for season and total amount spent on SNAP eligible items), SNAP recipients spent more on sugar-sweetened beverages ($1.05), red meat ($1.55), and cold convenience foods ($1.31) (though results are attenuated from the unadjusted model), and spent less on fruits ($1.49), vegetables ($1.33), and poultry ($1.19). Similar results are found in the adjusted model that was restricted to stores in low-income areas only.

Table 3.3. Association between SNAP receipt and dollar amount of grocery purchases, by food groups of interest.

	Model 1 (unadjusted)*	**Model 2 (adjusted)*[a]**	**Model 2 (low-income area stores only)*[b]**
	β (in $)	β (in $)	β (in $)
Beverages			
Sugar-sweetened beverage	1.45	1.05	1.07
Low-calorie beverage	0.05	-0.02	-0.01
Unsweetened beverage	0.27	-0.11	-0.08
100% Juice	0.09	-0.06	-0.06
Fruits, Vegetables, Legumes			
Fruit	-0.08	-1.49	-1.44
Vegetable	0.07	-1.33	-1.33
Bean	0.03	-0.02	-0.02
Nut or seed	-0.07	-0.21	-0.21
Main Protein Sources			
Red meat	4.44	1.55	1.42
Poultry	1.65	-1.19	-1.38
Seafood	0.25	-0.47	-0.45
Processed soy	-0.01	-0.03	-0.03
Processed meat	0.93	0.43	0.43
Eggs	0.03	-0.06	-0.06
Grains			
Bread	0.30	-0.11	-0.08
Cereal	0.24	0.05	0.06
Pasta, rice or other grain	0.25	0.04	0.04
Dairy			
Milk	0.33	0.10	0.09
Yogurt	-0.03	-0.22	-0.19
Cheese	0.36	-0.12	-0.11
Fats & Oils			
Fat or oil - liquid	0.01	-0.03	-0.03
Fat or oil - solid	0.10	0.00	-0.01
Desserts, Candy, Snacks			
Candy	0.16	0.04	0.05
Cold or frozen dessert	0.28	0.15	0.15

Table 3.3 (continued). Association between SNAP receipt and dollar amount of grocery purchases, by food groups of interest.

Sweet or salty snack	0.56	0.02	0.07
Sweet bread, cake, cookies	0.87	0.37	0.40
Prepared Foods			
Condiments, sauces, salad dressing	0.41	0.04	0.05
Soup	0.13	0.01	0.02
Pizza	0.33	0.26	0.26
Convenience food (cold)	1.87	1.31	1.37
Other			
Other food	0.43	0.04	0.00

*All results significant with p-value <.0001
[a] Adjusted for season and total dollar amount spent on SNAP-eligible items
[b] Restricted to stores with > median % of population below the Federal Poverty Line in the store's buffer area (based on average distance traveled to primary store to approximate the store's catchment area; sources: American Community Survey 2013; USDA; Rural Urban Community Area score)

Finally, we found that SSBs represented 5.35% of total SNAP sales in this database. According to the USDA's annual report, in fiscal year 2013 (the mid-point of the time period for which sales data were available) approximately $76 billion worth of SNAP benefits were redeemed across all authorized retailers (USDA Food and Nutrition Service, 2014). If we make the assumption that the composition of SNAP transactions are similar in these 188 stores as they would be in other supermarkets across the country during this two year period, we estimate that 4.1 billion dollars of the SNAP subsidies are spent on SSBs nationwide each year. This compares to $10.2 billion spent on fruits and vegetable and $26.3 billion spent on protein sources that include red meat, pork, poultry, seafood, eggs, and soy.

Discussion

In summary, several key differences were observed in spending patterns by SNAP status, in particular with respect to sugar-sweetened beverages, red meat and cold convenience foods (with SNAP shoppers purchasing more than non-SNAP shoppers), as well as fruits, vegetables and poultry (with SNAP shoppers purchasing less) after adjusting for season and total dollar amount spent on SNAP-eligible items. Patterns were similar when the analysis was restricted to low-income area stores only, suggesting that these disparities are related specifically to SNAP receipt.

Our rough estimate of SNAP spending on SSBs is higher than one previously published estimate (Andreyeva, Luedicke, Henderson, & Tripp, 2012b), but in line with others (Shenkin & Jacobson, 2010). In contrast to our estimate of $4.1 billion, Andreyeva and colleagues estimated that SNAP pays for $1.7 to 2.1 billion for sugary drinks (Andreyeva, Luedicke, Henderson, & Tripp, 2012a). This could be due in part to conservative assumptions used to develop their estimates (e.g. the assumption that SNAP households with young children in New England were representative of all SNAP households, and that spending in the first 6 months of the year are representative of the entire year). Using similar methods to our own, Shenkin and Jacobson estimated an annual SNAP expenditure of $4 billion on carbonated soft drinks (Shenkin & Jacobson, 2010). Our estimate is also based on certain assumptions, namely that spending at this supermarket chain in New England is representative of spending at all types of SNAP retailers nationally. Moreover, others have examined regional differences in SSB consumption among US adults and found variation including higher odds of consuming regular soda at least once per day in the South (Park, McGuire, & Galuska, 2015), indicating that our estimates may underestimate the total amount of SNAP dollars spent on SSBs nationally.

There are several strengths to this paper, including the use of sales data to establish shopping patterns among SNAP recipients. While previous studies have utilized participant self-report (Condon et al., 2015; Leung et al., 2012; 2013) or have analyzed sales data from a restricted population such as that of young families who have previously qualified for federal benefits (Andreyeva, Luedicke, Henderson, & Tripp, 2012a), there is a gap in the literature with respect to direct analysis of grocery sales data to establish shopping patterns of SNAP recipients vs. non-recipients in the general population.

Additional strengths include capturing seasonal variation with 25 months of data from multiple states with different SNAP distribution policies, and a diversity of stores in both rural and urban locations. Furthermore, we were able to utilize data from the American Community Survey to establish percent poverty levels within the catchment area of each store, enabling us to examine shopping patterns specifically for low-income stores.

There are also several limitations that should be acknowledged. First, there were unclassified UPCs in the database that we were unable to classify into food groups and thus were excluded from analysis (these represented 12% of UPCs and 11% of the total sales). Additionally, given that we did not have individually linked sales data we were unable to control for individual characteristics such as size of family. As an alternative we considered the % of each basket that is comprised of food types rather than make assumptions about consumption per person. Finally, we could not determine how SNAP beneficiaries' shopping patterns vary over the course of each month after receiving benefits. Previous work has observed a spike in spending by benefit recipients in the three days following benefit issuance (Wilde & Ranney, 2000), so there was likely some misclassification whereby those sales categorized as non-SNAP sales included people that do receive SNAP benefits but who ran out of benefits for a given month at the time of sale and therefore used an alternative form of payment (this would likely bias results towards the null because some people on SNAP potentially buying less healthy foods will be in the non-SNAP comparison group).

Conclusions

Overall, these findings help to establish current shopping patterns of SNAP recipients vs. non-recipients, and have important implications for potential modifications to the program. Modifications to SNAP policy such as disincentivizing SSB purchases and/or incentivizing healthier options could serve to address the disparity in dietary quality of grocery purchases by recipients. Future work should examine contextual factors, benefit issuance, and other aspects of the sales database to further inform the development of future community-based nutrition interventions.

References

Andreyeva, T., Luedicke, J., Henderson, K. E., & Tripp, A. S. (2012a). Grocery Store Beverage Choices by Participants in Federal Food Assistance and Nutrition Programs. *American Journal of Preventive Medicine*, *43*(4), 411–418.

Andreyeva, T., Luedicke, J., Henderson, K. E., & Tripp, A. S. (2012b). Grocery Store Beverage Choices by Participants in Federal Food Assistance and Nutrition Programs. *American Journal of Preventive Medicine*, *43*(4), 411–418.

Bartlett, S., Klerman, J., Olsho, L., Logan, C., Blocklin, M., Beauregard, M., et al. (2014). *Evaluation of the Healthy Incentives Pilot (HIP)* (pp. 1–582). Prepared by Abt Associates for the U.S. Department of Agriculture, Food and Nutrition Service.

Blumenthal, S. J., Hoffnagle, E. E., Leung, C. W., Lofink, H., Jensen, H. H., Foerster, S. B., et al. (2013). Strategies to improve the dietary quality of Supplemental Nutrition Assistance Program (SNAP) beneficiaries: an assessment of stakeholder opinions. *Public Health Nutrition*, *17*(12), 2824–2833.

Census.gov. (2016, April 3). American Community Survey (ACS). Retrieved April 3, 2016, from https://www.census.gov/programs-surveys/acs/

Condon, E., Drilea, S., Jowers, K., Lichtenstein, C., Mabli, J., Madden, E., & Niland, K. (2015). *Diet Quality of Americans by SNAP Participation Status:* (pp. 1–383). Prepared by Walter R. McDonald & Associates, Inc. and Mathematica Policy Research for the Food and Nutrition Service.

Fox, M. K., & Cole, N. (2004). *Nutrition and Health Characteristics of Low-Income Populations* (pp. 1–396). USDA Economic Research Service.

Hepps, D. (2015, August 4). Good Choice Criteria. Retrieved April 7, 2016, from http://www.nyc.gov/html/doh/downloads/pdf/home/good-choice.pdf

Lederer, A., Curtis, C. J., Silver, L. D., & Angell, S. Y. (2014). Toward a Healthier City. *American Journal of Preventive Medicine*, *46*(4), 423–428.

Leung, C. W., Blumenthal, S. J., Hoffnagle, E. E., Jensen, H. H., Foerster, S. B., Nestle, M., et al. (2013). Associations of Food Stamp Participation With Dietary Quality and Obesity in Children. *Pediatrics*, *131*(3), 463–472.

Leung, C. W., Ding, E. L., Catalano, P. J., Villamor, E., Rimm, E. B., & Willett, W. C. (2012). Dietary intake and dietary quality of low-income adults in the Supplemental Nutrition Assistance Program. *The American Journal of Clinical Nutrition*, *96*(5), 977–988.

Ludwig, D. S., Blumenthal, S. J., & Willett, W. C. (2012). Opportunities to Reduce Childhood Hunger and Obesity. *Jama*, *308*, 2567–2568.

Park, S., McGuire, L. C., & Galuska, D. A. (2015). Regional Differences in Sugar-Sweetened Beverage Intake among US Adults. *Journal of the Academy of Nutrition and Dietetics*, *115*(12), 1996–2002.

Shenkin, J. D., & Jacobson, M. F. (2010). Using the Food Stamp Program and Other Methods to Promote Healthy Diets for Low-Income Consumers. *American Journal of Public Health*, *100*, 1562–1564.

Simon, M. (2012). *Food Stamps Follow the Money* (pp. 1–28). Eat Drink Politics.

USDA ERS. (2016, April 3). Rural-Urban Commuting Area Codes. Retrieved April 3, 2016, from http://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/documentation.aspx

USDA Food and Nutrition Service. (2014). *SNAP Retailer Management 2013 Annual Report* (pp. 1–19).

Wilde, P. E., & Ranney, C. K. (2000). The Monthly Food Stamp Cycle: Shopping Frequency and Food Intake Decisions in an Endogenous Switching Regression Framework. *American Journal of Agricultural Economics*, *82*, 200–213.

Appendix. UPC categories

Category	Includes	Excludes	# of UPCs
BEVERAGES			
1. Sugary Drink	Soda, sport drink/enhanced drink, energy drink, sweetened tea or coffee drink, fruit juice/juice drink, vegetable juice, smoothie, hot chocolate, tonic water, bar mix, flavored milk or milk substitute	Meal replacement or nutrition supplement (e.g. Boost, Ensure), juice intended for cooking (e.g. lemon juice)	2836
2. Low-Calorie Drink	Diet, light, or low-calorie versions of drinks listed above		509
3. Unsweetened Drink	Unflavored water, seltzer, or soda water; coffee, tea, tea bags		1741
4. Alcohol	Beer, wine, liquor	Cooking wine	8418
5. 100% fruit juice	100% fruit juice		602
FRUIT, VEGETABLE, LEGUME			
6. Fruit	Fresh, frozen, canned, or pureed fruit	Maraschino cherry, fruit topping/sauce, fruit snack	1535
7. Vegetable	Fresh, frozen, canned, dried, or pureed vegetable	Dried herbs	2252
8. Bean	Black bean, black-eyed pea, chickpea, kidney bean, lentil, lima bean, navy bean, pinto bean, soy bean, split bean, white bean		422
9. Nut or seed	Nut, seed, or nut butter	Candied or chocolate-covered nut	612
MAIN PROTEIN SOURCES			
10. Red Meat	Beef, ham, lamb, pork, veal, game meat, ground meat or meat patty	Organ meat	1289
11. Poultry	Chicken, turkey, duck, ground poultry or poultry patty		346
12. Seafood	Fish, shellfish		960
13. Processed Soy/meat alternatives	Tofu, tempeh, seitan, any other meat alternatives including patties, burgers, sausages, deli meat		126
14. Processed Meat	Deli meat (processed roast beef, turkey, chicken, ham, salami, bologna), cured meat, bacon, sausage, hot dog, bratwurst		1198
15. Eggs/egg dishes	Eggs/egg dishes		135

Appendix (continued). UPC categories

GRAIN			
16. Bread	Loaf bread, sandwich thin, roll, tortilla, taco shell, wrap, pita, specialty bread (e.g. brioche, baguette), hamburger or hot dog bun, pizza crust, bagel, English muffin	Biscuits	1490
17. Cereal	Ready to eat cereal, hot cereal (e.g. oatmeal, grits, farina), granola		1021
18. Pasta, Rice, Or Other Grain	Pasta/noodle, rice, amaranth, barley, buckwheat, bulgur, whole cornmeal, emmer, faro, kamut, millet, whole rolled oats, quinoa, etc.		1648
DAIRY			
19. Milk or Milk Substitute	Unflavored liquid or powdered milk, soy milk, almond milk, rice milk	Coconut milk, buttermilk, condensed milk, evaporated milk, cream	448
20. Yogurt	Yogurt, kefir		602
21. Cheese	Cream cheese, cottage cheese, ricotta cheese, cheddar, mozzarella, feta, etc.	Cheese sauce	1238
FATS & OILS			
22. Fat or oil - solid	Butter, margarine, coconut oil		128
23. Fat or oil - liquid	Olive oil, pam spray, etc		197
DESSERTS, CANDY, SNACKS			
24. Candy	Candy, chocolate, gum, mint	Sugary topping (e.g. sprinkles, chocolate sauce)	2457
25. Cold or Frozen Dessert	Ice cream, frozen yogurt, whipped cream, popsicles		1261
26. Sweet or Salty Snack	Chips, pretzels, popcorn, granola/cereal bars, crackers, snack mix, pudding, dried fruit		3578
27. Sweet Bread, Cake, or Cookie	Sweet loaf (e.g. banana bread), cake, cinnamon roll, croissant, Danish, doughnut, muffin, breakfast pastry, cookie, brownie, pie, tart		3809

Appendix (continued). UPC categories

PREPARED FOODS			
28. Condiments, sauces & salad dressings	Dip, spread, salad dressing, hummus, guacamole, marinara sauce, seasoning packet for sauce/dressing/gravy, condiments		2880
29. Soup	Canned soup, soup mix, broth, base, ramen		856
30. Pizza	Frozen/refrigerated pizza, pizza ingredients sold as a kit	Pizza ingredients sold separately	321
31. Convenience Foods – cold	Prepared or packaged foods to be eaten away from the store, e.g. frozen meal, entrée, or side; boxed meal (e.g. rice dish or macaroni and cheese)		4734
32. Convenience Foods – hot	Deli foods, anything prepared/heated to eat at store		80
OTHER			
33. Other - food	herb, spice, or seasoning; baking ingredient; any food item not listed above		3011
34. Other - nonfood	Anything else not listed above		61584